



Rtadf: Testing for Bubbles with EViews

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Abstract

This paper presents **Rtadf** (**R**ight **T**ail **A**ugmented **D**ickey-**F**uller), an EViews Add-in that facilitates the performance of time series based tests that help detect and date-stamp asset price bubbles. Detection strategy is based on a right-tail variation of the standard Augmented Dickey-Fuller(ADF) test where the alternative hypothesis is of a mildly explosive process. The add-in implements four types of tests: Standard ADF, Rolling window ADF, supremum ADF (SADF) (Phillips, Wu, and Yu 2011) and generalized SADF (GSADF) (Phillips, Shi, and Yu 2013). Rejection of the null in each of these tests may serve as empirical evidence for an asset price bubble, and in the case of the SADF and GSADF tests, enables us, as a second step, to date-stamp its occurrence. The add-in calculates the relevant test statistics for each of the above four tests and simulates the corresponding exact finite sample critical values via Monte Carlo methods.

Keywords: Rational bubble, ADF test, Sup ADF test, Generalized Sup ADF test, Mildly explosive process, EViews.

1. Introduction

The recent global financial crisis was preceded by the bursting of the unprecedented US housing bubble. This fact reminds us all of the devastating implications of failing to recognize asset price bubbles in real time. Empirical identification of such bubbles in real time, and even in retrospect, is surely not an easy task, and it has been the source of academic and professional debate for many years.¹ One strand of the empirical literature suggests using time series estimation techniques while exploiting predictions made by finance theory in order to test for the existence of bubbles in the data. The main idea, based on asset pricing theory,

*Version 1.3, October 2, 2014.

¹There is a large amount of academic debate with regard to the theoretical plausibility of bubbles (Brunermeier 2008; Iraola and Santos 2008). This research deals with bubbles of the *rational* type (a.k.a., 'rational bubbles'), i.e., bubbles consistent with the rational expectations hypothesis (Blanchard and Watson 1983).

suggests that the existence of a bubble in an observed asset price should be manifested in its dynamics and its stochastic properties. More explicitly, theory predicts that if a bubble exists, prices should inherit its explosiveness property. This in turn enables formulating statistical tests which aim at detecting evidence of explosiveness in the data.²

One of the attempts to test for rational bubbles in the context of the stock market is found in [Diba and Grossman \(1988\)](#), where the authors suggest using reduced form stationarity tests with regard to stock prices and observable market fundamentals, and to rule out bubbles if the former is found no more explosive than the latter. [Evans \(1991\)](#) however, questions the power of such stationarity based tests in the presence of a periodically collapsing bubble (i.e., one that spontaneously occur and burst), an apparent feature of actual stock prices seen in the data. Using simulation methods, [Evans \(1991\)](#) shows that standard unit root and cointegration tests fail to reject the null of no bubble in the presence of periodically collapsing bubbles. Despite his findings, [Evans \(1991\)](#) leaves open the question of a better identification strategy.

More recently, new bubble detection strategies were developed and presented by [Phillips, Wu, and Yu \(2011\)](#), hereafter PWY) and [Phillips, Shi, and Yu \(2013\)](#), hereafter PSY). These strategies are based on recursive and rolling ADF unit root tests that enable us to detect bubbles in the data and to date-stamp their occurrence. These type of tests use a right tail variation of the Augmented Dickey-Fuller unit root test wherein the null hypothesis is of a unit root and the alternative is of a *mildly explosive* process.³ PWY and PSY show that using recursive and rolling tests results with higher power in the detection of bubbles, compared to standard tests on the whole sample. In a Monte Carlo study, [Homm and Breitung \(2012\)](#) compare several time series based tests for the detection of bubbles and find that the PWY strategy performs relatively well in detecting periodically collapsing bubbles and in real time monitoring. [Phillips et al. \(2013\)](#) show through a Monte Carlo study that the PSY strategy outperforms the PWY strategy in the presence of *multiple* bubbles.

A number of recent papers published implement the above mentioned bubble detection strategies in different contexts. For example, [Phillips and Yu \(2011\)](#) use the SADF test to date-stamp bubbles in the US housing market, corporate bond spreads and oil prices, during the global financial crisis. [Bettendorf and Chen \(2013\)](#) use the SADF and GSADF tests and find evidence for explosive behavior in the Sterling-Dollar exchange rate, though they conclude it is probably driven by fundamentals and not by a rational bubble. [Yiu, Yu, and Jin \(2013\)](#) apply the GSADF test Hong Kong residential property market and find evidence for multiple bubbles in the data.

This paper introduces **Rtadf**, an EViews Add-in that allows end-users to easily test for the existence of bubbles in the data by readily applying four variations of the right tail ADF unit root test, in line with the reduced form approach for bubble detection described above. Four tests include the standard ADF test and a rolling window ADF test, and the more recent PWY supremum ADF (SADF) test and the PSY generalized SADF (GSADF) test. The add-in capabilities include calculations of the relevant test statistic and the derivation of its corresponding critical values by Monte Carlo simulations

The rest of the paper is organized as follows. Section 2 presents a basic theoretical model of rational bubbles in a standard asset pricing model. Section 3 introduces the details of

²For recent surveys on econometric tests for bubbles see [Gürkaynak \(2008\)](#) and [Homm and Breitung \(2012\)](#).

³Limit theory for mildly explosive processes are developed in [Phillips and Magdalinos \(2007\)](#).

the econometric strategy used to detect explosive behavior in asset prices. Section 4 provides general instructions on how to use the **Rtadf** add-in within the **EViews** environment. Section 5 presents a hands-on illustration of **Rtadf**. Finally, Section 6 concludes.

2. Asset pricing with rational bubbles

This section present a simple asset pricing model to better understand the underlying rationale behind indirect (reduced form) time series tests for asset price bubbles. Under the no-arbitrage condition and the assumption of risk neutrality, in equilibrium, the price of an asset at time t equals the expected discounted payoff received at time $t + 1$

$$P_t = \frac{1}{R_{t+1}} E_t (P_{t+1} + D_{t+1}), \quad (1)$$

where P_t is the real stock price at time t , D_t is the dividend received for holding the stock from time $t - 1$ to t and R_t is the (gross) discount rate. Next, following [Campbell and Shiller \(1988\)](#) and [Cochrane \(2001\)](#) we obtain a log-linear approximation of Equation (1)

$$p_t = \kappa + \rho p_{t+1} + (1 - \rho) d_{t+1} - r_{t+1} \quad (2)$$

where $p_t \equiv \log(P_t)$, $d_t \equiv \log(D_t)$, $r_t \equiv \log(R_t)$, $\rho = 1 / \left[1 + e^{(\overline{p-r})} \right]$ with $\overline{p-r}$ being the average log price-to-dividend ratio, and

$$\kappa = -\log(\rho) - (1 - \rho) \log \left(\frac{1}{\rho - 1} \right).$$

Equation (2) is basically a first order differential equation. Solving Equation (2) by forward iteration and taking expectations yields the following log-linear approximation of the log price-to-dividend ratio:

$$p_t - d_t = \frac{\kappa}{1 - \rho} + \sum_{i=0}^{\infty} \rho^i E_t (\Delta d_{t+1+i} - r_{t+1+i}) + \lim_{i \rightarrow \infty} \rho^i E_t (p_{t+i} - d_{t+i}). \quad (3)$$

The right hand side of Equation (3) can be decomposed to two components,

$$p_t - r_t = f_t + b_t \quad (4)$$

where

$$f_t = \frac{\kappa}{1 - \rho} + \sum_{i=0}^{\infty} \rho^i E_t (\Delta d_{t+1+i} - r_{t+1+i}), \quad (5)$$

is the fundamental component, stated in terms of the expected dividend growth rate and expected returns, and where

$$b_t = \lim_{i \rightarrow \infty} \rho^i E_t (p_{t+i} - d_{t+i}), \quad (6)$$

is commonly referred to as the *rational* bubble component. The latter is the focus of the bubble tests described below.

Under the transversality condition, $\lim_{i \rightarrow \infty} \rho^i E_t p_{t+i} = 0$, and the possibility of a bubble is ruled out. Thus, the observed price equals the fundamental price. In contrast, the existence of a strictly positive bubble component, i.e., the situation where actual price exceeds what is implied by fundamentals, requires that investors expect to be compensated for overpayment (over the fundamental price) by the expected appreciation of the bubble component. In other words, investors are willing to pay a premium over the fundamental price only because they expect this premium to appreciate in the next period. Note that this behavior is completely consistent with the rational expectations assumption, hence the name 'rational bubble'.

More importantly, note that Equation (6) implies a submartingale property for b_t since

$$E_t(b_{t+1}) = \frac{1}{\rho} b_t = [1 + \exp(\bar{p} - \bar{d})] b_t, \quad (7)$$

where $[1 + \exp(\bar{p} - \bar{d})] > 0$. Thus, when $b_t \neq 0$, the log bubble component grows at rate g , where $g = \exp(\bar{p} - \bar{d}) > 0$.

This model reveals important insights regarding the stochastic properties of $p_t - d_t$, according to which, we can formulate an econometric test designed to rule out the presence of a rational bubble component in an observed asset price. To see this, note that the stochastic properties of $p_t - d_t$, implied by (3), are determined by those of f_t and b_t . In turn, the dynamics of f_t are determined by expected Δd_t and r_t . If d_t and r_t are *at most* $I(1)$ processes, evidence of explosiveness in $p_t - d_t$ (in this model) can only be the result of the presence of a bubble, i.e., $b_t \neq 0$. Thus, a test for the presence of a bubble can be formulated as a test for an explosive behavior in log price-to-dividend ratio, $p_t - r_t$.

3. Testing for bubbles

Following the conventions of PSY, assume the following random walk process with an asymptotically negligible drift:

$$y_t = dT^{-\eta} + \theta y_{t-1} + e_t, \quad e_t \stackrel{iid}{\sim} N(0, \sigma^2), \quad \theta = 1 \quad (8)$$

where d is a constant, η is a localizing coefficients that controls the magnitude of the drift as the sample size, T , approaches infinity and ε_t is the error term.⁴

Four test strategies implemented by the **Rtadf** add-in (which includes the ones suggested by PWY and PSY) are all based on some variation of the following reduced form empirical equation:

$$y_t = \mu + \delta y_{t-1} + \sum_{i=1}^p \phi_i \Delta y_{t-i} + \varepsilon_t. \quad (9)$$

where y_t is the variable in question (e.g., the price of a stock) μ is an intercept, p is the maximum number of lags, π_i for $i = 1 \dots p$ are the differenced lags coefficients and ε_t is the error term. Testing for a bubble (explosive behavior) is based on a right-tail variation of the standard ADF unit root test where the null hypothesis is of a unit root and the alternative is of a mildly explosive autoregressive coefficient. Formally, we test for

$$\begin{aligned} H_0 : & \delta = 1 \\ H_1 : & \delta > 1. \end{aligned}$$

⁴PSY set d , η and θ to unity, while PWY effectively set $\eta \rightarrow \infty$ (i.e., random walk without a drift).

Before proceeding to a description of the tests included in **Rtadf**, some notation is needed. For simplicity of exposition, we use a sample interval of $[0, 1]$ (i.e., we normalized the original sample by T). Denote by δ_{r_1, r_2} and by ADF_{r_1, r_2} the coefficient estimated by Equation (9) and its corresponding ADF statistic over the (normalized) sample $[r_1, r_2]$. In addition, denote by r_w the (fractional) window size of the regression, defined by $r_w = r_2 - r_1$ and by r_0 the fixed initial window, set by the user. The difference between the tests relates to the manner of setting r_1 and r_2 .

The first test included in **Rtadf** is a simple right-tailed version of the standard ADF unit root test. In this case, r_1 and r_2 are fixed to the first and last observations of the whole sample, respectively where in this case, $r_w = r_0 = 1$ (see Figure 1).⁵ However, the critical values for testing the null hypothesis differ from the ones used in the usual ADF unit root test since we now need the right tail of the statistic's nonstandard distribution.

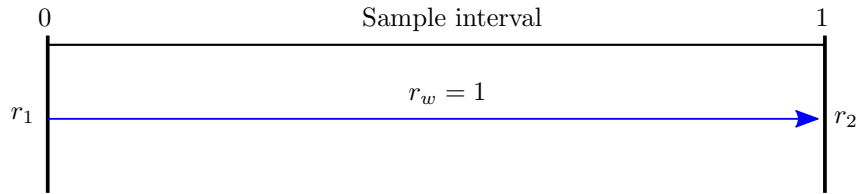


Figure 1: Illustration of the ADF procedure.

The second type of test, the rolling ADF (RADF) test, is a rolling version of the first test in which the ADF statistic is calculated over a rolling window of *fixed* size specified by the user, i.e., $r_w = r_0$ for all estimations. At each step of the RADF procedure, the window's start and end point (r_1 and r_2 respectively) are incremented one observation at a time (see Figure 2). Each estimation yields an ADF statistic, denoted as ADF_{r_1, r_2} . The RADF statistic is defined as the *supremum* ADF_{r_1, r_2} statistic among all possible windows.⁶

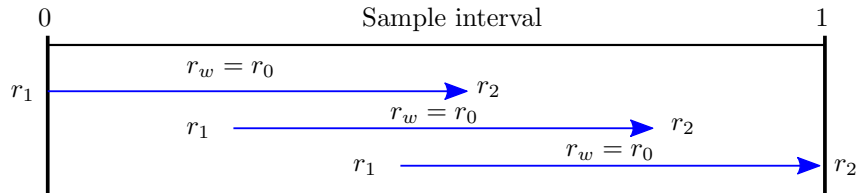


Figure 2: Illustration of the RADF procedure.

The SADF test, suggested by PWY, is based on recursive calculations of the ADF statistics with a fixed starting point and an expanding window, where the initial size of the window is set by the user. The estimation procedure goes as follows (see Figure 3): The first observation in the sample is set as the starting point of the estimation window, r_1 , i.e., $r_1 = 0$. Next, the end point of the initial estimation window, r_2 , is set according to some choice of minimal window size, r_0 such that the initial window size is $r_w = r_2$ (again, in fraction terms). Finally, the regression is recursively estimated, while incrementing the window size, $r_2 \in [r_0, 1]$, one observation at a time. Each estimation yields an ADF statistic denoted as ADF_{r_2} . Note that

⁵The t -statistic from this test matches the one reported by **EViews**.

⁶Note that the windows in the RADF procedure are overlapping.

in the last step, estimation will be based on the whole sample (i.e., $r_2 = 1$ and the statistic will be ADF_1). The SADF statistic is defined as the *supremum* value of the ADF_{r_2} sequence for $r_2 \in [r_0, 1]$:

$$SADF(r_0) = \sup_{r_2 \in [r_0, 1]} \{ADF_{r_2}\} \quad (10)$$

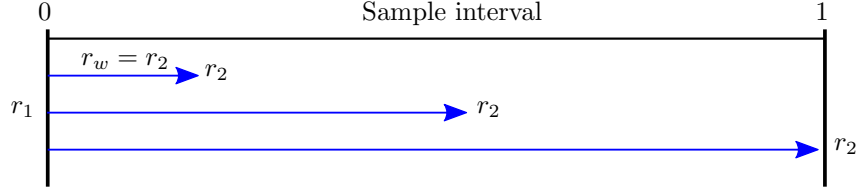


Figure 3: Illustration of the SADF procedure.

The fourth and last test is the generalized SADF (GSADF), suggested by PSY. This test generalizes the SADF test by allowing more flexible estimation windows, wherein, unlike the SADF procedure, the starting point, r_1 , is also allowed to vary within the range $[0, r_2 - r_0]$ (see Figure 4). Formally, the GSADF statistic is defined as

$$GSADF(r_0) = \sup_{\substack{r_2 \in [r_0, 1] \\ r_1 \in [0, r_2 - r_0]}} \{ADF_{r_1}^{r_2}\} \quad (11)$$

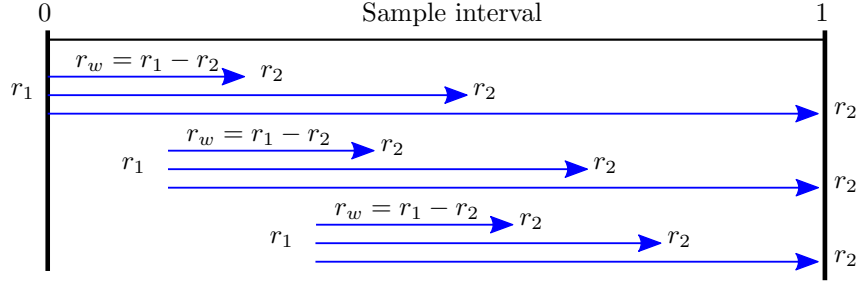


Figure 4: Illustration of the GSADF procedure.

3.1. Date-stamping bubble periods

As PWY and PSY show, the SADF and GSADF procedures can also be used, under general regularity conditions, as a date-stamping strategy that consistently estimate the origination and termination of bubbles. In other words, if the null hypothesis of either of these test is rejected, one can estimate the start and end points of a specific bubble (or bubbles). The date-stamping procedures will now be presented in brief.⁷

The first date-stamping strategy is based on the SADF test. PWY propose comparing each element of the estimated ADF_{r_2} sequence to the corresponding right-tailed critical values of the standard ADF statistic to identify a bubble initiating at time Tr_2 . The estimated

⁷For a detailed presentation see [Phillips et al. \(2011\)](#), [Phillips and Yu \(2011\)](#) and [Phillips et al. \(2013\)](#).

origination point of a bubble is the first chronological observation, denoted by T_{r_e} , in which ADF_{r_2} crosses the corresponding critical value (from below), while the estimated termination point is the first chronological observation after T_{r_e} , denoted by T_{r_f} , in which ADF_{r_2} crosses below the critical value. Formally, the estimates of the bubble period (as fractions of the sample) are defined by

$$\hat{r}_e = \inf_{r_2 \in [r_0, 1]} \left\{ r_2 : ADF_{r_2} > cv_{r_2}^{\beta_T} \right\} \quad (12)$$

$$\hat{r}_f = \inf_{r_2 \in [\hat{r}_e, 1]} \left\{ r_2 : ADF_{r_2} < cv_{r_2}^{\beta_T} \right\} \quad (13)$$

where $cv_{r_2}^{\beta_T}$ is the $100(1 - \beta_T)\%$ critical value of the standard ADF statistic based on $[Tr_2]$ observations.^{8,9}

Similarly, the estimates of the bubble period based on the GSADF are given by

$$\hat{r}_e = \inf_{r_2 \in [r_0, 1]} \left\{ r_2 : BSADF_{r_2}(r_0) > cv_{r_2}^{\beta_{Tr_2}} \right\} \quad (14)$$

$$\hat{r}_f = \inf_{r_2 \in [\hat{r}_e, 1]} \left\{ r_2 : BSADF_{r_2}(r_0) < cv_{r_2}^{\beta_{Tr_2}} \right\} \quad (15)$$

where $cv_{r_2}^{\beta_T}$ is the $100(1 - \beta_T)\%$ critical value of the sup ADF statistic based on $[Tr_2]$ observations. $BSADF(r_0)$ for $r_2 \in [r_0, 1]$, is the backwards sup ADF statistic that relates to the GSADF statistic by noting that

$$GSADF(r_0) = \sup_{r_2 \in [r_0, 1]} \{ BSADF_{r_2}(r_0) \}. \quad (16)$$

4. Instructions

4.1. Installation

In essence, **EViews** Add-ins are **EViews** programs packed in a way that makes them feel and look like built-in **EViews** procedures.¹⁰ This relatively new feature enables adding procedures and functionalities that have yet to be implemented in official releases of **EViews**. By using the Add-ins feature and program language, the user is able to augment standard written programs with interactive user interface, thus making them more general purposed and user friendly. Moreover, unlike regular **EViews** programs, add-ins have the ability to run directly from **EViews** objects and/or by commands.

EViews add-ins are available for **EViews** users with versions 7.1 and above. Installing the **Rtadf** add-in (or any other add-ins for that matter) on an existing copy of **EViews** can be done manually by downloading the self extracting installation file from the download section

⁸In order to asymptotically eliminate type I errors there is a need to let $\beta_T \rightarrow 0$ as $T \rightarrow 0$. However in applied work it is convenient to use a constant β_T such as 5%.

⁹Phillips and Yu (2011) argue that the dating rule requires that the duration of the bubble be non-negligible. In Phillips *et al.* (2013) the authors define $\log(T)/T$ as a minimal lasting time for a bubble period.

¹⁰To R users, the concept is similar to R packages as with MATLAB users and tool-boxes.

at the EViews website at <http://www.eviews.com/Addins/addins.shtml> where it is listed under **Rtadf***.¹¹ Alternatively, EViews users with version 8, can download the add-in while inside EViews by clicking **Add-ins** → **Manage Add-ins**, selecting the **Rtadf** add-in from the list presented under the **Available** tab and clicking the **Install** button. In general, note that all other add-ins available in the list, are written either by the EViews staff or by outside users.

Each Add-in published on the EViews website (including **Rtadf**) has a corresponding support thread in the EViews Add-in Support forum, which can be found at <http://forums.eviews.com/viewforum.php?f=2>.

4.2. Using the add-in

The **Rtadf** add-in can only be run from a series object. Initiating the add-in's dialog box is done by opening a series object and then clicking **Proc** → **Add-ins** → **Right Tail ADF tests**. The test dialog box, presented in Figure 5 enables the user to set the sample period, type of test, initial window size (as a fraction or number of observations), deterministic terms in the test equation and the information criteria for selecting the number of lags in the ADF equation (p in Equation 9). In addition, it allows the user to choose the option of simulating critical values for the test (thus prompting the simulation dialog box described below) and whether to view a graph of the sequence of ADF statistics, the corresponding critical value sequence and the actual series.

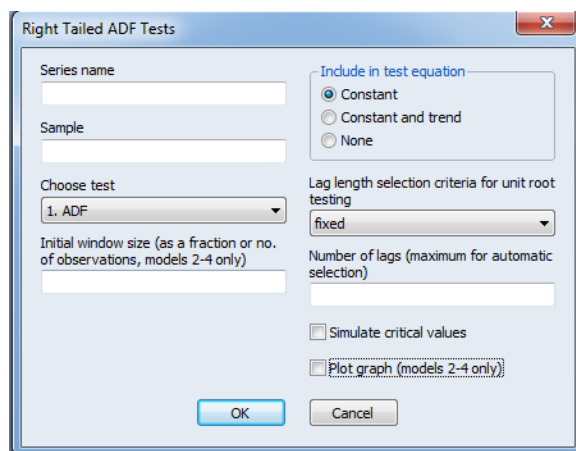


Figure 5: Dialog box.

Toggling the “simulate critical values” option prompts the simulation dialog box, presented in Figure 6. Simulations for all four tests are performed according to the following steps:

1. Draw one realization at length T based on the null model (given by Equation (8)).
2. Estimate Equation 9 by OLS and store the relevant test statistic (ADF/RADF/SADF/GSADF).
3. Repeat steps 1 and 2 N times (where N is a large number, say 2,000.)

¹¹The asterisk next to the add-in's name indicates the add-in was developed by an EViews user rather than by IHS EViews.

4. Calculate the 90%, 95% and 99% quantiles of the distribution of the relevant statistic.

Quantiles calculated in step 4 can then be used for testing the null of unit root against the alternative of an explosive process. In addition, the simulation output includes the p -value of the test statistic, defined as the probability of observing a statistic as extreme as we did under the null, calculated as

$$p(\hat{\tau}) = \frac{1}{N} \sum_{j=1}^N I(\tau_j > \hat{\tau}), \quad (17)$$

where $\hat{\tau}$ is the estimated test statistic (ADF, RADF, SADF or GSADF), N is the number of replications, $I(\cdot)$ denotes the indicator function which is equal to 1 if the argument is true and 0 otherwise and τ_j are the simulated test statistics ($j = 1, \dots, N$). The sequences of critical values, which are necessary for the date-stamping procedure, are also derived as a by-product of the recursive and rolling simulations.

Simulation setup in **Rtadf** is very flexible, allowing the user to specify the type of test, appropriate sample size, number of replications, number of run-in observations, deterministic terms in the test equation, initial window size, significance level for the critical value sequence (i.e., β), specification for the parameters of the data generating process for the null hypothesis (i.e., set values for d , η and θ in Equation (8)). In addition the user can choose whether to use T or Tr_w in the null model when calculating the simulated critical value sequence (the later is more accurate but can be very time consuming for large samples while the former is less accurate but faster).¹² As mentioned previously, the output of the simulation procedure is the 90, 95 and 99 percent quantiles of the finite sample distribution of the statistic in question, the relevant p -value of the test statistic and the relevant critical values sequence for the date-stamping process.

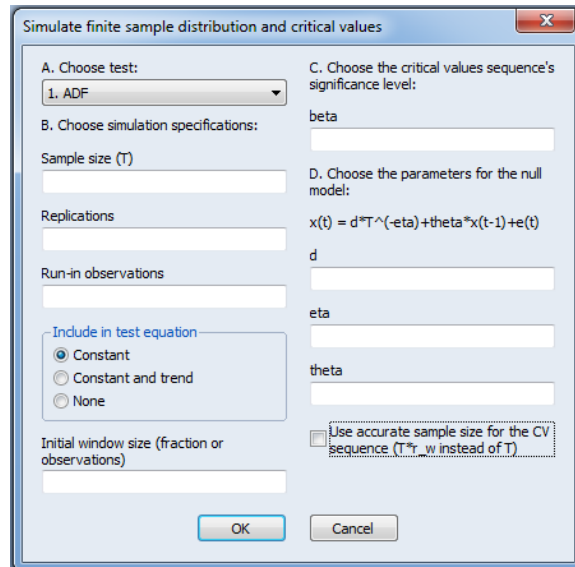


Figure 6: Critical values simulation dialog box.

¹²Note that by default, sample size and the initial window size used in the previous step are shown in the simulation dialog box.

4.3. Usage via a command line

The **Rtadf** add-in can also be called upon via a command line. This feature enables using the add-in's capabilities as an integrated part of other EViews programs. The syntax is given by:

`series_name.rtadf(options)`

Basic options	
<code>const (default)</code>	Include a constant in the test equation.
<code>trend</code>	Include a constant and a linear time trend in the test equation.
<code>none</code>	Do not include a constant or time trend.
<code>info = arg (default = 'fixed')</code>	Either fixed or information criterion to use when computing automatic lag length selection: 'aic' (Akaike), 'sic' (Schwarz), 'hqc' (Hannan-Quinn), 'maic' (Modified Akaike), 'msic' (Modified Schwarz), 'mhqc' (Modified Hannan-Quinn).
<code>lag = integer (default = '0')</code>	Either a fixed number of lags (if 'fixed' is chosen for the 'info' option) or maximum lag length to consider when performing automatic lag length selection.
Test options	
<code>model = integer (default = 1)</code>	Type of test: '1' (ADF), '2' (RADF), '3' (SADF), '4' (GSADF)
<code>win = number (default=0.1)</code>	Initial window size (in fraction terms or in number of observations).
Simulation options	
<code>sim</code>	Simulate critical values.
<code>rep = integer (default=1000)</code>	Simulation's number of replications.
<code>d = number (default=1)</code>	See Equation (8).
<code>eta = number (default=1)</code>	See Equation (8).
<code>theta = number (default=1)</code>	See Equation (8).
<code>beta = [0,1] (default=0.95)</code>	Significance level for the critical values sequence. (see section 3.1.)
<code>Trw</code>	Use Tr_w instead of T (default) for calculating of the sequence of critical values.
Other options	
<code>graph</code>	Create a graph of the results.
<code>print</code>	Print output from the test.

Table 1: Options for the command line.

where the available options are detailed in table 1. Next, we show a couple of command line examples. First, the command:

`snp.rtadf(const,model=3,print)`

performs an SADF test on the series SNP with the test equation including a constant term and prints the results. Second, the command:

```
nasdaq.rtadf(trend,model=4,info=aic,lag=4,win=0.02,sim,rep=2000,graph,print)
```

performs a GSADF test on the series NASDAQ with the test equation including a constant term and a linear time trend and an initial window size of 2% of the sample, simulates critical values using 2000 replications, generates a graph and prints the results.

5. Illustration

We now demonstrate in detail how to use **Rtadf** by replicating the results of the SADF test, reported in Phillips *et al.* (2013), Table 8 (pp. 33) and Figure 8 (pp. 35). The analysis is based on monthly data of the S&P 500 price-dividend ratio (the series object name in this example is SNP) over the period of 1871:M1 to 2010:M12 that include 1680 observations, see Figure 7.¹³

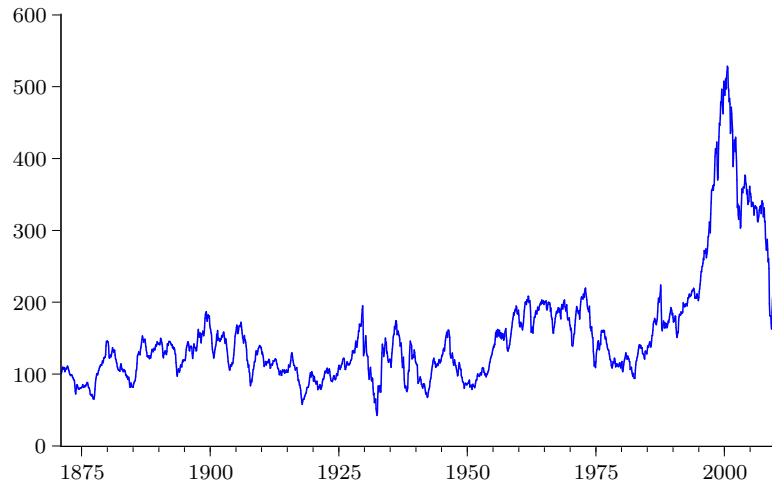


Figure 7: S&P 500 price-dividend ratio, 1871:M1–2010:M12.

In order to start the bubble detection process with the price-dividend ratio (SNP) series, first open the SNP series object and then click **Proc** → **Add-ins** → **Right tail ADF tests** (see Figure 8). Next, specify the test parameters as in PSY, see Figure 9(a) and then click the **OK** button. Note that just like in PSY, the initial window size is set to 36 observations (which constitutes approximately 2% of the whole sample), the lag length of the ADF test (p in Equation 9) is set to zero. Make sure that the “simulating critical values” option is checked so that the output includes the necessary critical values for testing the null hypothesis.

Simulation parameters’ specifications are also set in accordance with PSY by adjusting the parameters in the simulation dialog box, which prompts right after clicking the **OK** button in the main dialog box, see Figure 9(b). Clicking **OK** results in finite sample critical values for the conduction the SADF test.¹⁴

¹³The data used by the authors can be downloaded from <https://sites.google.com/site/shupingshi/PrgGSADF.zip?attredirects=0>.

¹⁴The simulation in this example may take a while since it involves running $(1680 - 36) \times 2000 = 3,288,000$ regressions. (On our Intel Core i5 with 4GB of memory it took over an hour.)

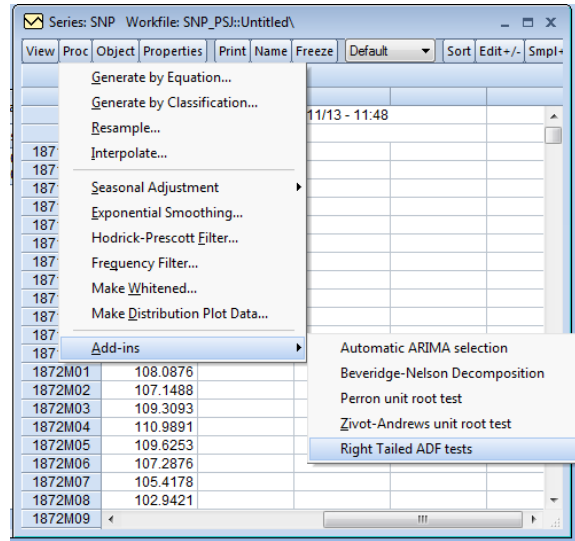
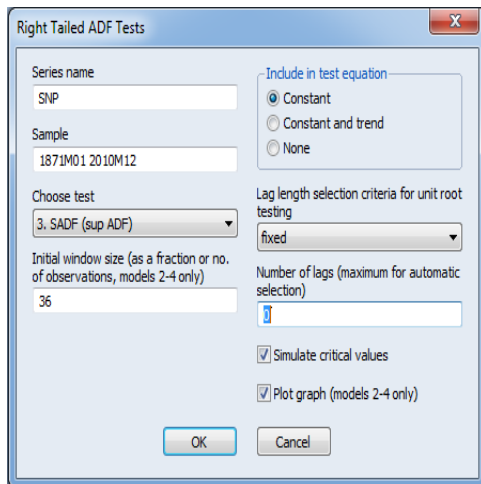
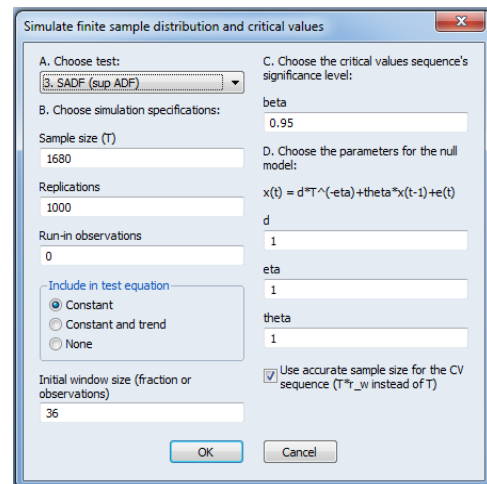


Figure 8: S&P 500 SADF proc menu.



(a) Test dialog box.



(b) Simulation dialog box.

Figure 9: Parameter settings for the S&P 500 SADF test and simulation.

Summary output of the SADF test is displayed in Figure 10(a). The output is presented within the series object and it includes two panels.¹⁵ The top panel is a table that holds the estimated SADF t -statistic followed by the corresponding (right tail) 90%, 95% and 99% critical values derived from the simulated statistic's distribution. Note that the sup value of this sequence is 3.443, whereas in Phillips *et al.* (2013) it equals 3.30. However, using the MATLAB code published by the authors, gives an SADF statistic that equals 3.443.¹⁶ The simulated critical values, which appear below the SADF statistic, match exactly those in PSY,

¹⁵In this example, the output was extracted to an EViews spool object by clicking on the 'Freeze' button.

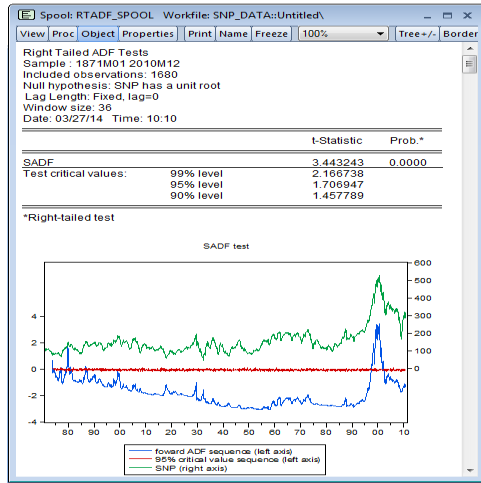
¹⁶The add-in's estimate of the GSADF statistic for the SNP series (not shown) is the same as the one in PSY (2013).

Table 8.

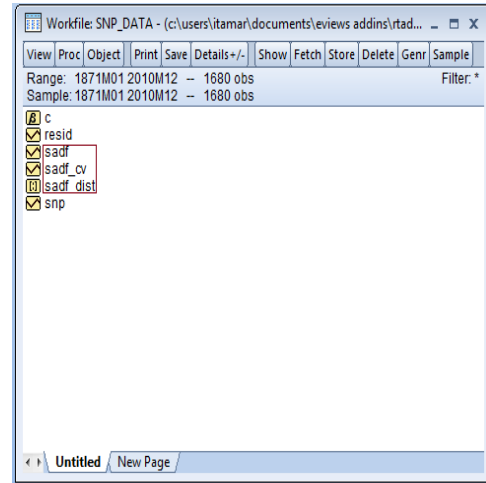
Period No.	PSY (2013)	Rtadf
1	1879:M10–1880:M4	1879:M5–1880:M4
2	1997:M07–2001:M8	1997:M7–2002:M5

Table 2: Comparison of date-stamping procedures results.

The bottom panel of the spool presents the date-stamping procedure for the SADF test. The graph includes the SNP series (in green), the ADF_{r_2} statistic sequence (in blue) and the corresponding 95% critical values sequence (in red). The data used to plot the graph are now available as series objected within the workfile under the names 'sadf' (the blue line) and 'sadf_cv' (the red line), see Figure 10(b).¹⁷ The add-in successfully identifies two bubble periods, just like in PSY, though with minor differences in the start and end point (see Table 2). In addition, the add-in identifies one bubble period lasting four months in the beginning of the sample and a couple of 'blips' of bubbles lasting for one observation (i.e., one month). The source of discrepancy might be due to differences in the random number generator used by each software. However, if we ignore “too-short-lasting” bubble periods (PSY recommend to restrict identification to ones lasting more than $\log(T)$ units of time measures, which in this case equals $\log(1680) \approx 7$ months), the results are very similar. Note that the whole proce-



(a) Outpout spool.



(b) Workfile with the added series. (marked with the red rectangle.)

Figure 10: S&P 500 SADF output.

cedure described in this section can be accomplished via the execution of a single command line:

¹⁷The names of these series will change according to the test we use. For instance, if we will apply the GSADF test, the output will include two new series objects named 'gsadf' (the sequence of the BSADF statistics values) and 'gsadf_cv' (the sequence of the corresponding critical values). Note that each run of the test runs over the previous output. Hence, if there is a need to save these series, copy them under different names.

```
snp.rtaadf(model=3,win=36,sim,rep=2000,Trw,graph,print)
```

Concluding the illustration, the SADF test results point to the presence of *at least* one bubble in the S&P 500 price index at the 1% significance level (since $3.443 > 2.141$). However, since there seem to be evidence for at least two bubble periods (1879-80 and 1997-2002), as a second step (which is not perused here), there is a justification to use the GSADF test.

6. Concluding remarks

This paper presents a new EViews add-in, **Rtaadf**, that implements newly developed asset price bubble detection strategies, all based on right tail versions of the standard reduced form ADF unit root test, where the null of unit root is tested against the alternative of a mildly explosive process. In this case, rejection of the null for a specific time series may serve as evidence of an asset price bubble.

This paper began with a short background on the methodological developments of reduced form econometric approaches for bubble detection alongside a theoretical asset pricing model which helps to clarify the rationale behind the reduced form approach. Next, we gave a brief technical discussion on the bubble detection tests included in **Rtaadf**, and finally, a simple illustration of using the add-in in the context of the S&P 500 stocks index was presented.

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References

- Bettendorf T, Chen W (2013). “Are there Bubbles in the Sterling-Dollar Exchange Rate? New Evidence From Sequential ADF Tests.” *Economics Letters*, **120**, 350–353.
- Blanchard OJ, Watson MW (1983). “Bubbles, Rational Expectations and Financial Markets.”
- Brunnermeier MK (2008). “Bubbles.” In SN Durlauf, LE Blume (eds.), *The New Palgrave Dictionary of Economics*. Palgrave Macmillan, Basingstoke.
- Campbell JY, Shiller RJ (1988). “The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors.” *Review of financial studies*, **1**(3), 195–228.
- Cochrane J (2001). *Asset Pricing*. Princeton University Press.
- Diba BT, Grossman HI (1988). “Explosive Rational Bubbles in Stock Prices?” *The American Economic Review*, **78**(3), 520–530.
- Evans GW (1991). “Pitfalls in Testing for Explosive Bubbles in Asset Prices.” *The American Economic Review*, **81**(4), 922–930.

- Gürkaynak R (2008). “Econometric Tests of Asset Price Bubbles: Taking Stock.” *Journal of Economic Surveys*, **22**(1), 166–186.
- Homm U, Breitung J (2012). “Testing for Speculative Bubbles in Stock Markets: A Comparison of Alternative Methods.” *Journal of Financial Econometrics*, **10**(1), 198–231.
- Iraola MA, Santos MS (2008). “Speculative Bubbles.” In SN Durlauf, LE Blume (eds.), *The New Palgrave Dictionary of Economics*. Palgrave Macmillan, Basingstoke.
- MATLAB (2010). *version 7.10.0 (R2010a)*. The MathWorks Inc., Natick, Massachusetts.
- Phillips PCB, Magdalinos T (2007). “Limit Theory for Moderate Deviations from a Unit Root.” *Journal of Econometrics*, **136**(1), 115–130.
- Phillips PCB, Shi S, Yu J (2013). “Testing for Multiple Bubbles 1: Historical Episodes of Exuberance and Collapse in the S&P 500.”
- Phillips PCB, Wu Y, Yu J (2011). “Explosive Behavior in the 1990s NASDAQ: When Did Exuberance Escalate Asset Values?” *International Economic Review*, **52**(1), 201–226.
- Phillips PCB, Yu J (2011). “Dating the Timeline of Financial Bubbles During the Subprime Crisis.” *Quantitative Economics*, **2**(3), 455–491.
- Quantitative Micro Software (2013). *Eviews, Version 8*. Irvine CA, USA. URL <http://www.eviews.com>.
- R Core Team (2012). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL <http://www.R-project.org/>.
- Yiu MS, Yu J, Jin L (2013). “Detecting Bubbles in Hong Kong Residential Property Market.” *Journal of Asian Economics*.

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